K-Nearest Neighbors

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IIT Gandhinagar

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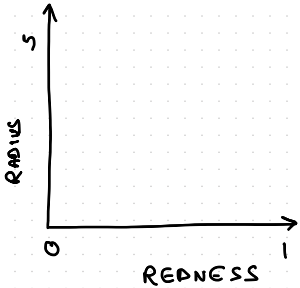
CLASSIFICATION



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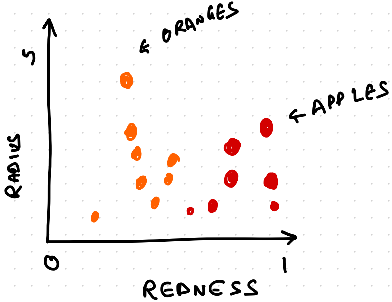

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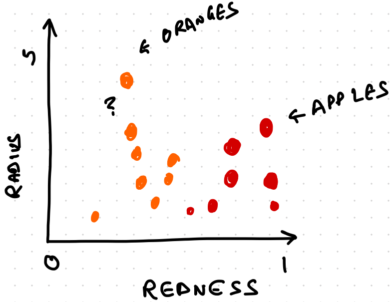

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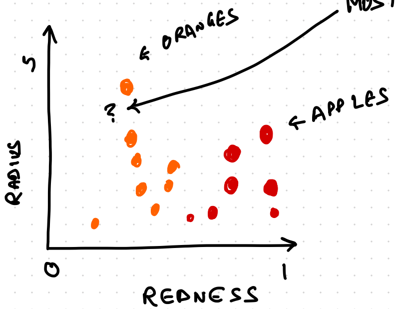
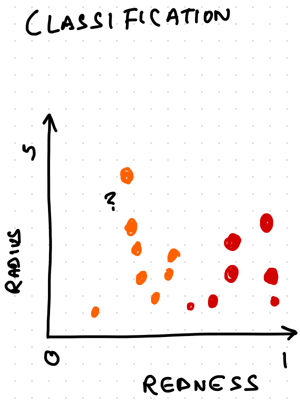
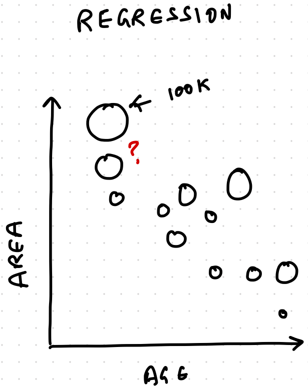
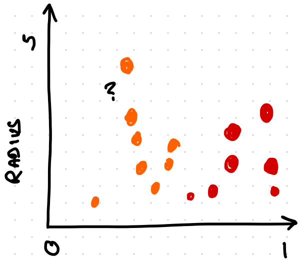


MOST LIKELY
AN
ORANGE
∵ "SIMILAR"
TO
ORANGES
IN
ATTRIBUTES


CLASSIFICATION
5
?
RADIUS
0
1
REDNESS

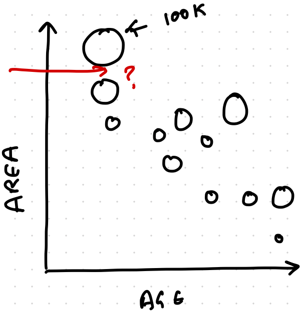

REGRESSION
100K
?
AREA
AGE

CLASSIFICATION

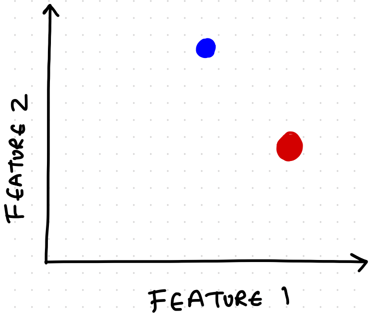


REGRESSION

LIKELY CLOSE to 100K AS "SIMILAR" TO HOMES OF THAT PRICE



VORONOI DIAGRAM FOR 1-NN



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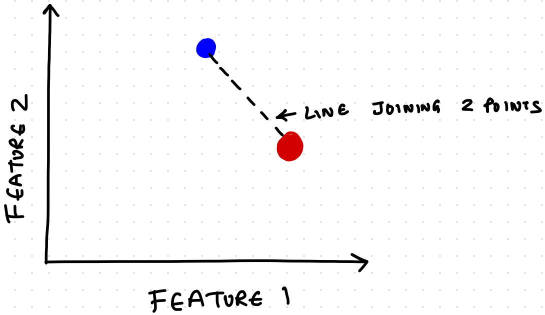

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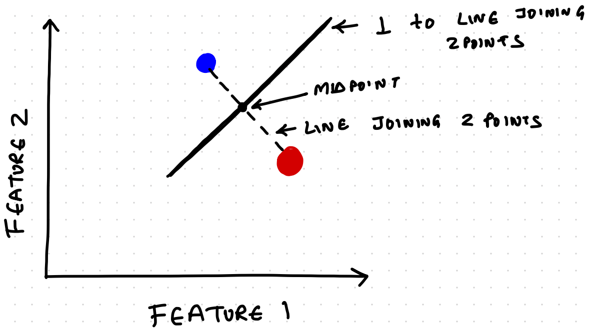

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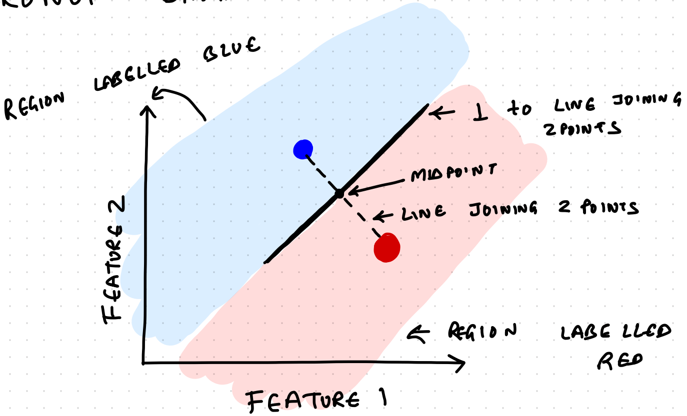

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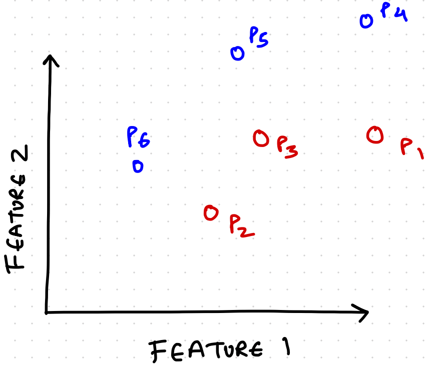

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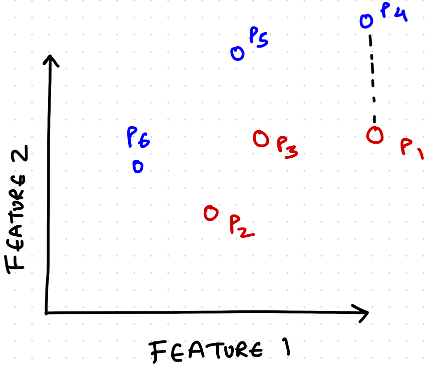
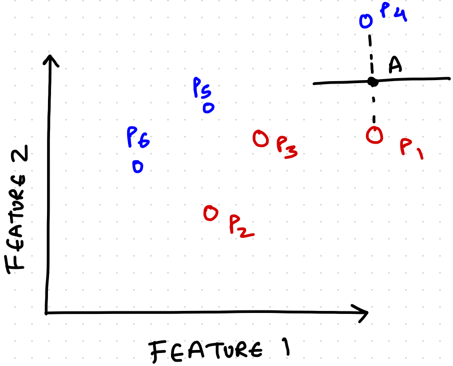


VORONOI DIAGRAM FOR 1-NN

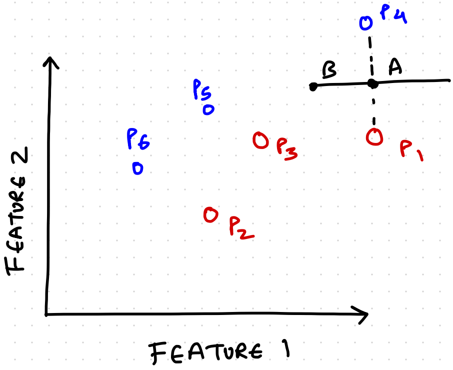
A: MID PT B/W P_1 & P_4



VORONOI DIAGRAM FOR 1-NN

A: MID PT B/W P_1 & P_4

B: CLOSER TO P_3 than P_1



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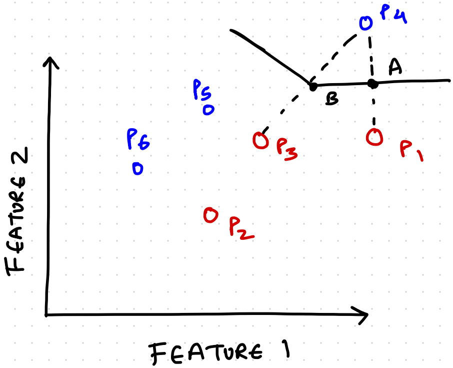
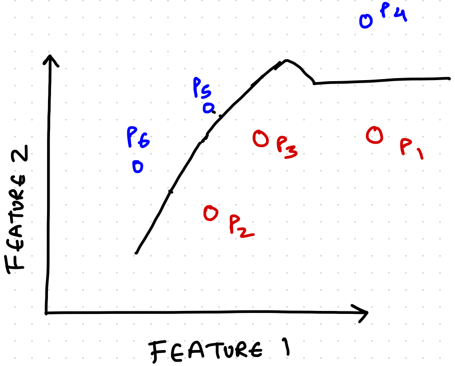


VORONOI DIAGRAM FOR 1-NN

DECISION BOUNDARY IS PIECE-WISE LINEAR



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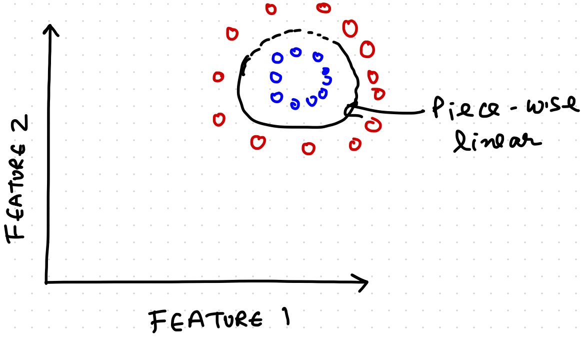
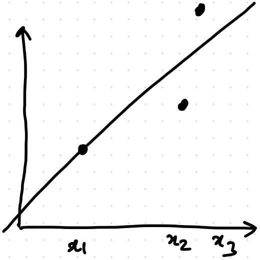
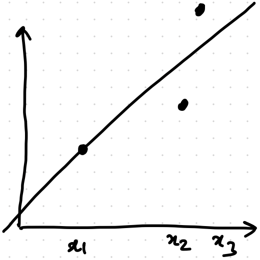


LINEAR REGRESSION



1NN REGRESSION

LINEAR REGRESSION



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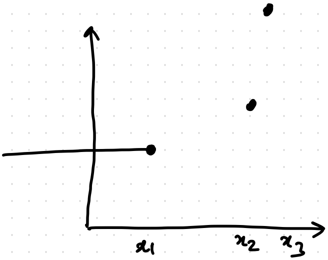
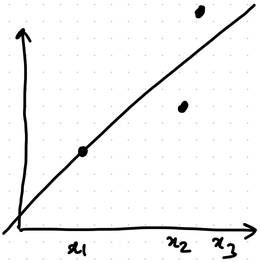


$x < x_1$: NN is (x_1, y_1)

LINEAR REGRESSION



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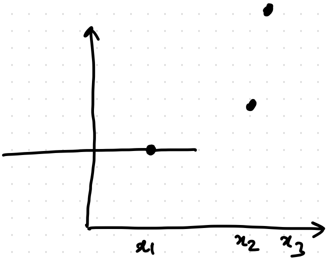
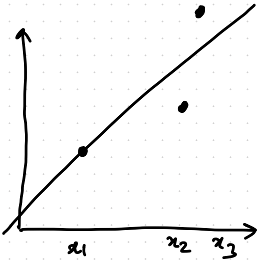


$x < x_1$: NN is (x_1, y_1)

$x < \frac{x_1+x_2}{2}$: NN is (x_1, y_1)

LINEAR REGRESSION



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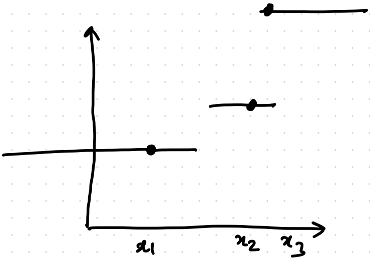

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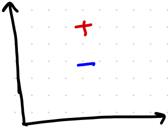
$x < \frac{x_1 + x_2}{2}$: NN is (x_1, y_1)

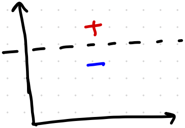
$\frac{x_1 + x_2}{2} < x < \frac{x_2 + x_3}{2}$: NN is (x_2, y_2)

KNN IS NON-PARAMETRIC



LINEAR MODEL

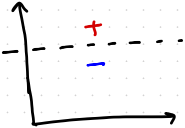
KNN IS NON-PARAMETRIC



LINEAR MODEL

DECS^n BOUNDARY $y = mx + c$ (# params = 2)

KNN IS NON-PARAMETRIC



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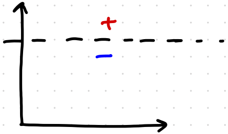
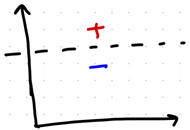
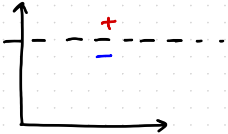


KNN (K=1)

Decs^n BOUNDARY (LIKE $y = mx + c$)

KNN IS NON-PARAMETRIC





LINEAR MODEL

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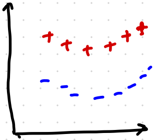
KNN (K=1)

DECS^n BOUNDARY (LIKE $y = mx + c$)

ADD DATA



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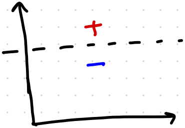
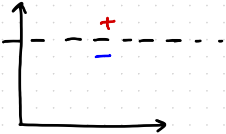


LINEAR MODEL

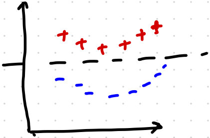
DECS^{N} BOUNDARY $y = mx + c$ (# params = 2)



KNN (K=1)

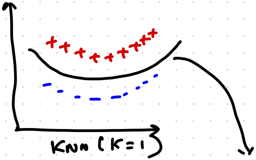
DECS^{N} BOUNDARY (LIKE $y = mx + c$)

ADD DATA



LINEAR MODEL

DECS^{N} BOUNDARY $y = mx + c$ (2 params)



KNN (K=1)

PARAMS >> 2 (AT LEAST CUBIC)

PARAMETRIC

#PARAMS FIXED
WRT DATASET SIZE

MAKE ASSUMPTIONS
(LIKE FUNCTIONAL FORM)

USUALLY QUICKER

Eg: LINEAR MODELS,
SVM (LINEAR, POLYNOMIAL)

NON-PARAMETRIC

PARAMS GROWS
WRT DATASET SIZE

LESSER ASSUMPTIONS

USUALLY SLOWER

Eg: KNN, DT,
SVM (with
RBF)

Parametric vs Non-Parametric Models

	Parametric	Non-Parametric
Parameter	Number of parameters is fixed w.r.t dataset size	Number of parameters grows w.r.t. to an increase in dataset size
Speed	Quicker (as the number of parameters are less)	Longer (as number of parameters are less)
Assumptions	Strong Assumptions (like linearity in Linear Regression)	Very few (sometimes no) assumptions
Examples	Linear Regression	KNN, Decision Tree

Lazy vs Eager Strategies

	Lazy	Eager
Train Time	0	$\neq 0$
Test	Long (due to comparison with train data)	Quick (as only "parameters" are involved)
Memory	Store/Memorise entire data	Store only learnt parameters
Utility	Useful for online settings	
Examples	KNN	Linear Regression, Decision Tree

Important Considerations

- What are the **features** that will be considered for data similarity?

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- What is the **aggregation function** that is going to be used?
- What are the **number of neighbors** that you are going to take into consideration?
- What is the **computational complexity** of the algorithm that you are implementing?

Important Considerations: Distance Metric

The Distance Metric acts as a *measure of similarity* between the points.

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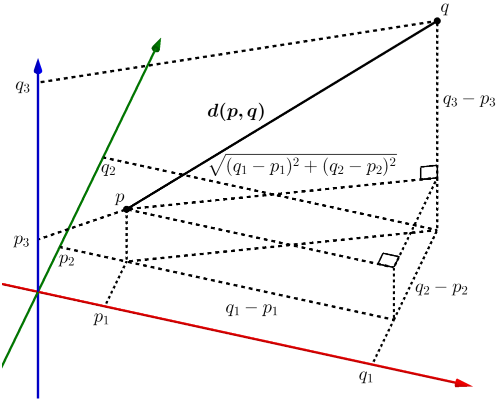

Euclidean Distance

Important Considerations: Distance Metric

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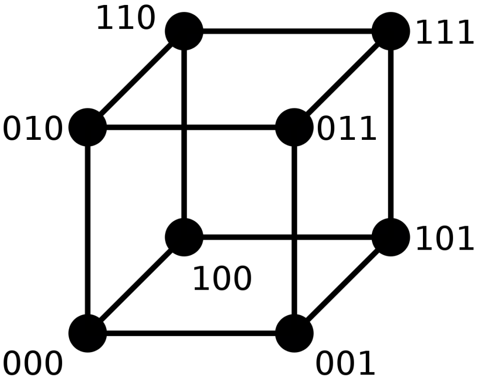

Hamming Distance

Important Considerations: Distance Metric

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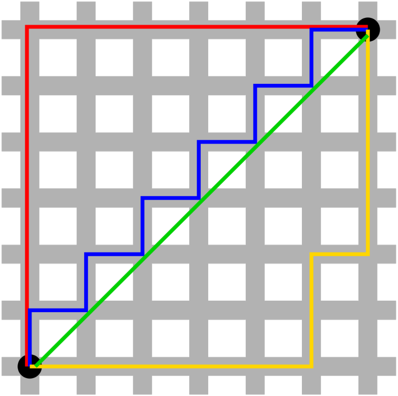

Manhattan Distance

Important Considerations: Value of K

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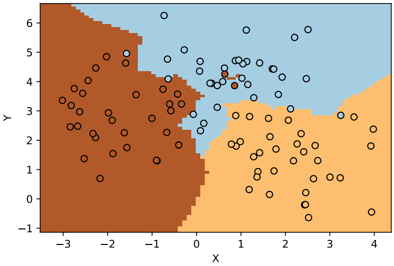
Low values of K will result in each point having a very high influence on the final output $\implies$ noise will influence the result
High values of K will result in smoother decision boundaries
$\implies$ lower variance but also higher bias

Important Considerations: Value of K

Important Considerations: Value of *K*



K = 3

Important Considerations: Value of K

Aggregating data

There are different ways to go about aggregating the data from the K nearest neighbors.

- Median

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- Median
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- Mode

KNN Algorithm

- Keep the entire dataset: (x, y)

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- For a query vector q:

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KNN Algorithm

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  2. Predict y^*

Curse of Dimensionality

With an increase in the number of dimensions:

Curse of Dimensionality

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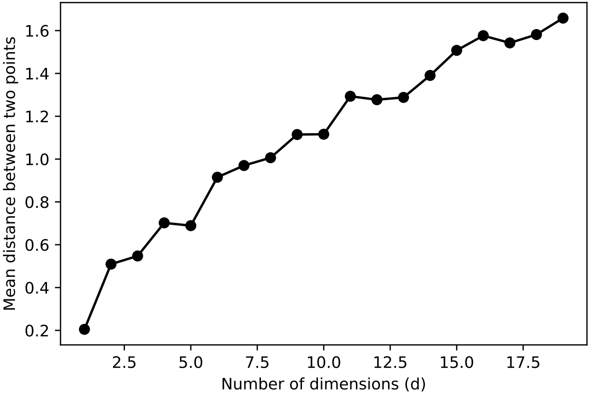
1. the distance between points starts to increase



For a unifromly random dataset

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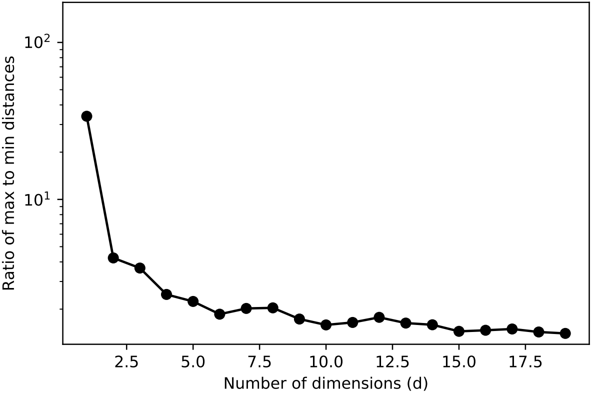

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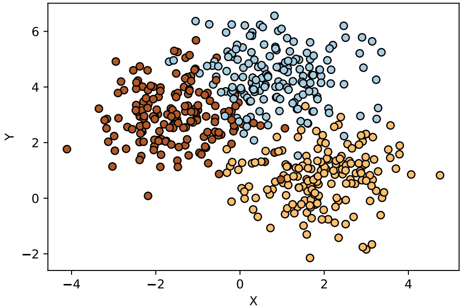
Approximate Nearest Neighbors

Doing an exhaustive search over all the points is time consuming, especially if you have a large number of data points.



Example of a big dataset

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Such techniques include:

- Locality sensitive hashing

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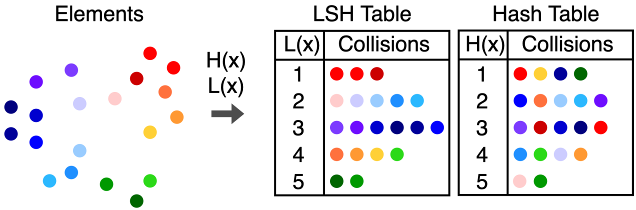
If you are willing to sacrifice accuracy there are algorithms that can give you improvements that go into orders of magnitude.
Such techniques include:

- Locality sensitive hashing
- Vector approximation files
- Greedy search in proximity neighborhood graphs

Locality sensitive hashing

Normal hash functions $H(x)$ try to keep the collision of points across bins uniform.



Example of a big dataset

Locality sensitive hashing

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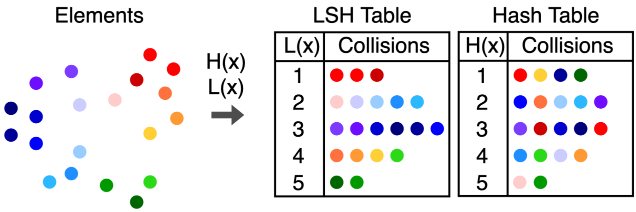
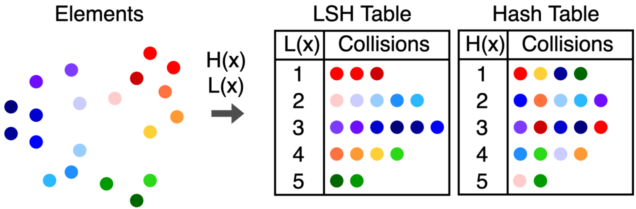
A locality sensitive hash (LSH) function $L(x)$ would be designed such that similar values are mapped to similar bins.



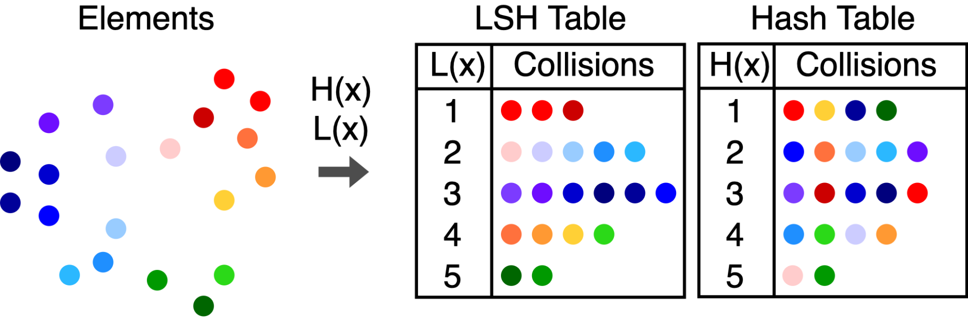
Example of a big dataset

Locality sensitive hashing

A locality sensitive hash (LSH) function $L(x)$ would be designed such that similar values are mapped to similar bins.
For such cases, all elements in a bin would be given the same label, which again can be decided on the basis of different aggregation methods



Example of a big dataset


Elements
H(x)
L(x)
LSH Table
L(x)
Collisions
1
2
3
4
5
Hash Table
H(x)
Collisions
1
2
3
4
5

Pop Quiz: KNN Concepts

1. What happens to KNN performance as *k* approaches *n* (total data points)?

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- **Scalability**: Approximate methods needed for large datasets